

ROBOTIC MANIPULATOR CONTROL BY USING MACHINE

LEARNING ALGORITHMS: A REVIEW

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ABSTRACT

Robotic field has emerged as the most important technological development in human life. Robotic systems are used as surgical equipment as the design precision of systems has become very accurate. In this scenario the robotic manipulator design is crucial. Artificial neural networks have become popular in the field of robotics. In designing the robots and robotic manipulators the machine learning techniques is playing a vital role in giving the high accurate output. In this paper, different machine learning algorithms are discussed in the scenario of robotic system design.

KEYWORDS: Robots, Artificial Neural Networks, Surgical Equipment & Algorithms

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1. INTRODUCTION

Robotic applications have become the part of human life. The applications include farming and agriculture [1], Cleaning purposes [2], medical and surgical [3], digging operations [4], in an industrial application[5], cleaning and inspection of high rise buildings [6], the metallic skeleton of bridges [7], welding and manipulation in construction[8], rescue operation applications in military and civil[9,10].

Machine learning methods have been generally connected in an assortment of territories, for example, pattern recognition. With machine learning systems, PCs are blessed with the capacity of acting without being unequivocally customized, building calculations that can gain from the information, and settling on information driven choices or expectations. Amid the previous decades, machine learning brings gigantic influence on our day by day existence with illustrations, including efficient web look, self-driving frameworks, PC vision, and optical character recognition. All things considered, with regards to the human data handling systems (e. g. discourse and vision), the execution of customary machine learning methods is a long way from tasteful.

The advancements in computing machines have shown a new path for optimization with different techniques. The continuous stream of data has to be evaluated at regular intervals to find the status of process control and monitoring. In mechanical engineering, the machine learning concept can be applied in manufacturing, robotics, automobiles, etc. The optimization techniques in machine learning are giving good results in achieving a

better throughput. In the new era the words Artificial intelligence, machine learning and neural networks are used extensively, but there is a little variation among them.

Artificial Intelligence is a computing system that is as good as humans to perform specific tasks. A robot can be thought of a machine with artificial intelligence. Machine learning is a way to achieve the artificial intelligent system. The neural networks are one the model of machine learning to develop and intelligent system.

Machine learning basically consists of data collection, data pre-processing, pattern training and pattern testing. Machine learning techniques are divided as three different techniques

- Supervised learning
- Unsupervised learning
- Reinforcement learning

All the techniques involve two phases

- Training
- Testing.

The data input of the system is divided into training and testing before building the model. Generally 70% for training and 30% for testing is used. To train the model perfectly, the training data and testing data may be interchanged or one can use a method K-fold to separate the data into training set and testing set. Once the system is trained with the training data and testing inputs will be applied to the system to validate and to find the accuracy.

Supervised learning techniques require input data and output for which the data is associated. Examples of Supervised Learning: k- nearest neighbour classifier, Regression methods, Decision Tree, Random Forest, KNN, Logistic Regression[11] etc. For the unsupervised learning only input is available and these will be clustered by using unsupervised learning algorithms. Examples are Apriori algorithm, K-means[12].

In the reinforcement learning, the machine trains itself from the input data. The machine trains from the past experience. Markov Decision Process is an example of reinforcement learning

2. DECISION TREE

This is One Kind of the Supervised Machine Learning Technique. This Can Be Used for Both Binary and Continuous Classifications. It is a Graph Like Structure and This Algorithm Splits the Variables Into Homogeneous Sets and Finds the Tree for the Classification. A Decision is Made Based on Input Given for the Tree. Intelligent Robot System Was Developed [13] By a Decision Tree Algorithm Based Learning System. This System Performs Incremental Learning In Real Time and Helps Designing an Evolutionary Decision Tree Method in the Limited Memory of An Embedded System. Applications of Decision Trees are Also Found In Soccer Robot Design [14, 15]. An Alternative Method of Decision Tree which is Called as Behaviour Tree Also Has Been Used in Many Robotic Applications [16]. The Figure 1 Shows the Behaviour Tree Which is Used in [16] For Pick And Place Task.

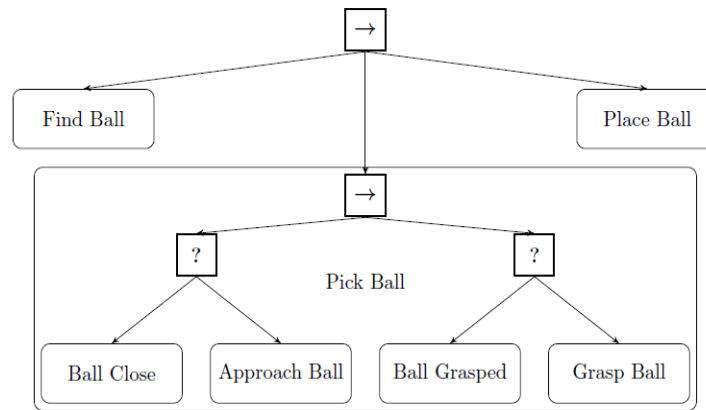


Figure 1: Behaviour Tree for Pick and Place Task.
(Courtesy Michele Colledanchise [14])

3. SVM (Support Vector Machine)

It is a classification method. In this algorithm, binary classification is performed in general. The Support vector machine provides different kernels such a regression.

A data driven fault diagnosis method for service robot was developed by suing SVM. A novel training technique was implemented by using SVM, for improving the training speed, on one hand sample reduction was performed [17].

SVM is used for classification tasks to control the industrial robots from the user's thoughts [18]. This system can also be used for pick and place robots. For 3D control, it requires a multimodal system.

A Hybrid architecture of SVM with particle swarm optimization and fuzzification improves the tracking control of robotic manipulators significantly [19]

In a five bar linkage robotic manipulator, the trajectory control and tracking with SVM techniques have shown a better result [20]. Intelligent techniques like neural network and support vector machines based on the controllers have been proposed to generate the precise control of robotic manipulators for trajectory tracking. A five bar linkage manipulator has been chosen for simulation purpose. Results have shown that SVM has the best tracking accuracy amongst all the controllers of the paper.

4. NEURAL NETWORKS IN ROBOTIC MANIPULATORS

Neural networks have been used in robotic manipulators to get accurate results. Figure 2 shows the neural network employment in controlling the manipulator. In this section, one of the popular neural network model in robotics is discussed.

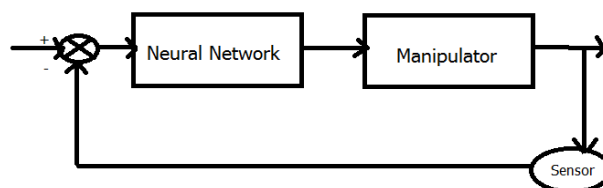


Figure 2: Training of Neural networks

Radial basis function is a single hidden layer network. It nonlinear classifier at the hidden layer, but the output

layer is linear. It uses different activation functions, namely Gaussian, thin plate Spline, Quadratic and inverse quadratic activation functions. Out of these Gaussian is more popular activation function.

The Gaussian radial basis function can be given by

$$f(k) = \exp(-k^2 / 2\sigma^2)$$

Where $k = \|x - c_i\|$ which is the Euclidian distance between input and center of the unit.

And the output is calculated as $y(x) = \sum_{i=0}^m f_i w_i$, where w_i is the weight matrix.

For the solution of problems in dynamic and kinematics of robot manipulators, the radial basis function were proved to be good [21]. The nonlinear dynamics are compensated using RBFNs in robotic contour control [22]. The negative effect of friction is cancelled by adopting radial basis functions for two joint-manipulator [23]. The improved RBF with dynamic region was proposed in control robot manipulator with stability analysis using Lyapunov function [24]. The terminal sliding-mode control to robotic manipulator along with actuator dynamics is developed by using RBFNs [25]

Neural networks are also have been used in robot path planning. A modified Q-learning algorithm which is inspired from the biological neural network for robot path planning by Ni et al [26] a combination of fuzzy, wavelets and neural network for the tracking and control of mobile robots [27]. The artificial neural networks with different activation functions have been reported for mobile robot control, tracking and also have achieved a better result [28-29]. The neural network had been a better choice in car automation system [30-31]. It was also reported that the improved speech recognition systems for robotics can be built by modification of neural by the use of deep learning [32-33].

5. CONCLUSIONS

The robots are able to travel in all spatial directions and planes to perform inspection and maintenance operations of infrastructures. (bridges, offshore platforms). The robotics manipulators can be controlled by machine learning techniques. In this paper, applications of machine learning techniques in robotic manipulator are reviewed. The techniques like decision tree, support vector machines are used in robotic applications. The neural networks are used in the control of robotic manipulators.

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